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13. ABSTRACT ***(Maximum 200 Words)***

This grant had three specific aims.

AIM 1: Transcending the serial/parallel dichotomy in visual search: Guided Search, our model of human visual search behavior, has proposed that "preattentive" visual processes guide the deployment of attention from item to item in a serial, item-by-item fashion. Others have proposed parallel models of search. Our new model, Guided Search 4.0 and our data attempt to reconcile these views. It is a hybrid model in which a serial bottleneck governs selection of some visual objects for further processing. Visual processing before and after the bottleneck can be characterized as parallel.

AIM 2: Understanding the role of memory in visual search: We have found visual search for targets proceeds without memory for rejected non-targets. This claim runs counter to the "common sense" observation that we direct real-world search strategically. "I have looked there. Now I will look here." New work replicates our findings and shows that the common-sense, memory processes are quite slow and, thus, often not useful in laboratory search tasks.

AIM 3: The relationship of different modes of attentional control. Finally, we report on a series of experiments that show how visual search can occur at the same time as other visual tasks.

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Introduction

In this report, we will summarize the work supported by AFOSR over the past few years. Producing a report of vast length does not seem advisable, so the emphasis is on the word "summarize". We would, of course, be happy to provide great detail about any of the projects described here. The report will be organized around the three aims of the grant. Within each aim, we will organize the information around the papers and manuscripts that have resulted from this work.

AIM 1: **Transcending the serial/parallel dichotomy in visual search:** Guided Search, our model of human visual search behavior, has proposed that "preattentive" visual processes guide the deployment of attention from item to item in a serial, item-by-item fashion. Others have argued for deployment of attention to multiple items in parallel. These views have been seen as opposed to one another. The work in this aim is intended to reconcile them in a single framework.

The primary synthesis of our current views on "Guided Search" can be found in:

Wolfe, J. M. (2007). Guided Search 4.0: Current Progress With A Model Of Visual Search. In W. Gray (Ed.), *Integrated Models of Cognitive Systems* (pp. 99-119). New York: Oxford.

Our primary interest is in visual search tasks. These are tasks where an observer looks for some target in a display containing distractors. "Classic" Guided Search (Wolfe, 1994; Wolfe, Cave & Franzel, 1989) is a two-stage model of visual search. With support from AFOSR, we developed Guided Search 4.0 (GS4). The basic architecture is shown here:

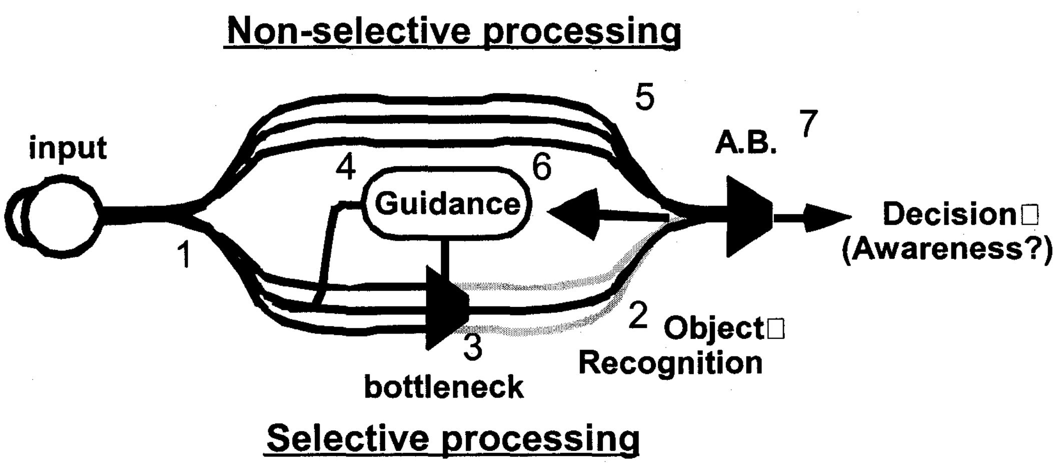

Figure One: The large-scale structure of GS4. See text for details.

Using the numbers on the figure as reference: Parallel processes in early vision (1) provide input to object recognition processes (2) via a mandatory selective bottleneck (3). The

parallel processes can provide information about a limited set of attributes (Wolfe & Horowitz, 2004). Below, we discuss our most recent contributions to the understanding of that set. The bottleneck allows one "preattentive object file" (Wolfe & Bennett, 1997) at a time to pas to the object recognition processes at a rate of about one every 50 msec. Another way to describe this is that the front-end of the system creates a "priority map" (Serences & Yantis, 2006) that represents the preattentive guess about the likely location(s) of targets. The bottleneck represents a winner-take-all (WTA) process that passes the most likely item to the next stage. (For recent evidence for the WTA nature of selection, see Zénon, Hamed, Duhamel & Olivier, 2009)

We model object recognition as a diffusion process (Ratcliff, 1978; Ratcliff, Gomez & McKoon, 2004). The details of object recognition are outside the scope of our work (and a very hard problem, altogether). Diffusion of the information required to identify a target takes place over several hundred msec. This means that, although items are selected into the object-recognition diffuser one at a time, several objects will be in the process of being identified at the same time. As a consequence, GS4 is a hybrid serial/parallel model (Moore & Wolfe, 2001; Wolfe, 2003).

As noted, the guidance in Guided Search is the use of information from early visual processes to guide access to the selective bottleneck (3). In GS4, guidance is imagined as a control device, sitting to one side of the pathway from input to object recognition (4). The reason for this is that the properties of guidance turn out to differ from the processes that give rise to perception and this is hard to explain if guidance is in the main pathway. To give a very recent example, we have had Os search for desaturated (e.g. pink, light blue) targets among saturated (e.g. red, blue) and white distractors. We carefully equated the perceptual distances between targets and distractors. Thus, the perceptual distance from pink to white was the same as the perceptual distance from light blue to white, for example. Interestingly, search for pink among red and white was hundreds of msec faster than search for light blue among blue and white (Kuzmova et al., 2008). For present purposes, the point is that pink's ability to guide differs from its perceptual salience.

GS1-GS3 were single pathway models. In GS4, we model visual processing as having two pathways: a selective pathway and a non-selective pathway (5). The non-selective pathway is not subject to the bottleneck in the selective pathway (3). It is capable of processes like analysis of texture statistics (Ariely, 2001) (Chong & Treisman, 2003) and even some crude semantic analysis of scenes ("beach" or "city street", not "corner of 4th and Main") (Oliva & Torralba, 2001) (Oliva 2005; Potter, Staub, & O'Connor, 2004). It is not capable of object recognition (Evans & Treisman, 2005) (Walker, Stafford, & Davis, 2008). There is support for these ideas in recent neural data (Peelen, Fei-Fei, & Kastner, 2009).

It is probable that some relatively late information, perhaps semantic information, can influence guidance (6). Examples include (Henderson, Brockmole, Castelhano, & Mack, 2007; J. M. Henderson & Ferreira, 2004; Hidalgo-Sotelo, Oliva , & Torralba, 2005; Vo & Henderson, 2009). This is implied in models like Ahissar and Hochstein's "Reverse Hierarchy Model" (Ahissar & Hochstein, 2004; Hochstein & Ahissar, 2002). We continue to investigate this topic.

GS4 envisions at least two bottlenecks in processing since the selective bottleneck in visual search (3) seems to be separable from the bottleneck (7) that produces effects like the attentional blink ("AB" in the figure, see Shapiro, 1994). For example, while some scene processing may be possible via a non-selective pathway, perception of that scene seems to be fully blocked by the attentional blink (Marois, Yi, & Chun, 2004)

The GS4 chapter describes the results of simulations that mimic the main results of visual search experiments. Notably, it produces RT distributions that are qualitatively similar to the data. Part of our work has been to better characterize RT distributions in search. This work is summarized in two papers:

Palmer, E. M., Horowitz , T. S., Torralba, A., & Wolfe, J. M. (2009). Response Time Distributions in Visual Search Tasks - I: What Do RT Distributions Really Look Like? *J. Exp. Psychol: Human Perception and Performance, submitted*

Palmer, E. M., Horowitz , T. S., & Wolfe, J. M. (2009). Response Time Distributions in Visual Search Tasks II: Non-Parametric Response Time Distribution Normalization. *J. Exp. Psychol: Human Perception and Performance, submitted*

There is theoretically useful information in the distribution of reaction times in visual search tasks. However, two difficulties stand in the way of exploiting RT distributions. First, there are too few trials in a typical dataset and second, unlike means, RT distributions are not trivial to combine across observers. We addressed both of those problems in a pair of papers. First, we collected a very large data set, running ten observers on 1000 trials at each of 4 set sizes in each of three search tasks: The search tasks were a *feature* search, with the target defined by color; *conjunction* search, with the target defined by a combination of color and orientation; and *spatial configuration* search, where the target was a 2 among distractor 5s.

This large data set allows us to characterize the RT distributions in detail. Figure 2 (from the paper) shows the individual target present and absent distributions for ten observers performing the conjunction task:

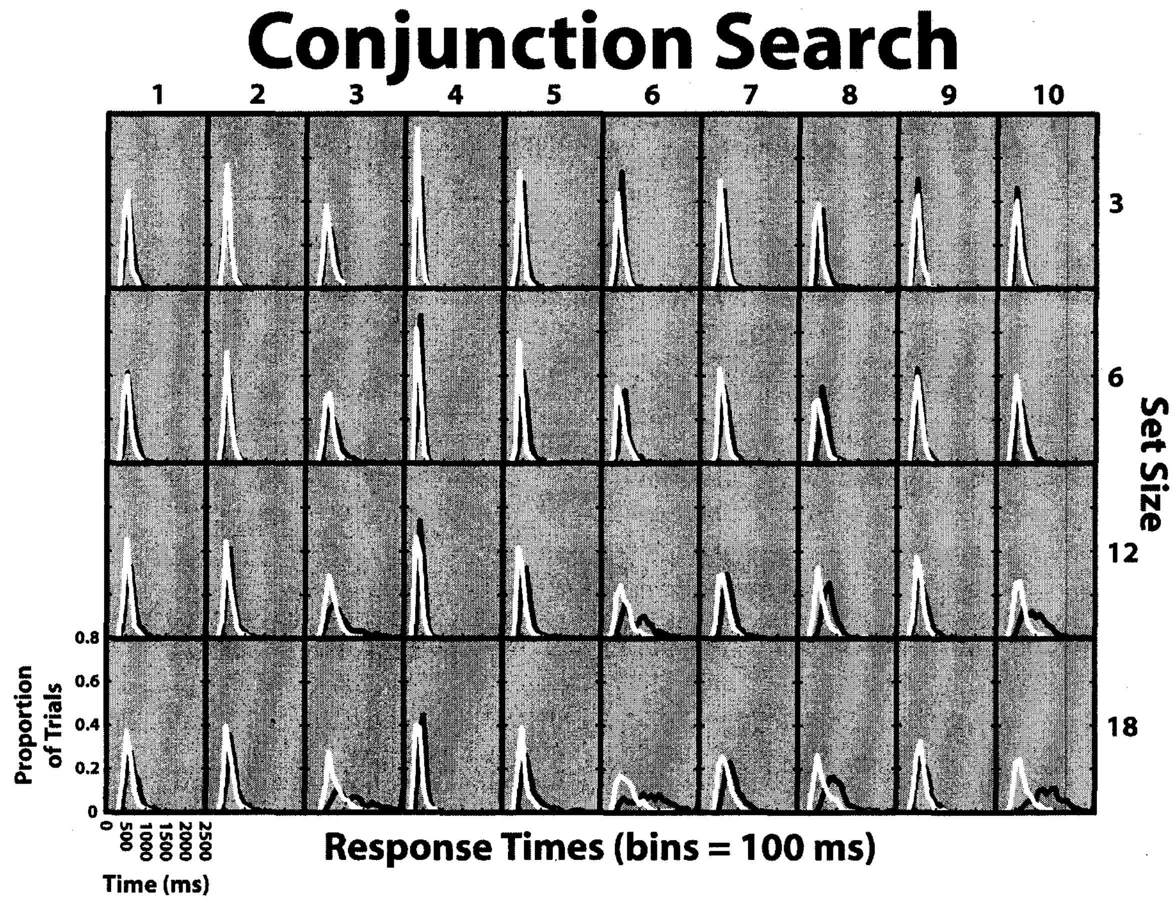

Figure Two: Set size versus response time.

Note that the distributions all have similar positively skewed forms. White lines are target present distributions. Black lines are target absent. Moreover, the present and absent distributions tend to overlap extensively (in ways that are puzzling from the point of view of the effort to model target-absent trials).

We fit several psychologically motivated functions (ex-Gaussian, ex-Wald, Gamma, and Weibull) to the data. All fit reasonably well so if a model had a theoretically motivated reason to believe that the distribution should have a specific form, these data would be supportive. That said, it is not obvious that these distributions should be fit by any very simple function. After all, the RT will be the product of, at least, initial visual processing, search, and the motor output. Each of these processes will have its own temporal character and there is no reason to assume that the concatenation of the processes will result in some simple distribution. Of more importance are the more qualitative statements that can be made on the basis of the RT distribution data.

In order to make such statements, we developed a non-parametric normalization procedure, the "x-score transform", that allows us to compare distributions via quantile alignment. The x-score transform aligns the 25^{th} and 75^{th} percentiles of a distribution to any two arbitrary values (e.g., -1 and +1, respectively). This procedure removes linear scaling

differences in distributions while preserving non-linear properties such as skew and kurtosis. The x-score transform tends to isolate the shapes of distributions regardless of their original mean and variance. In the second RT distribution paper, we applied the x-score transform to the distributions from feature, conjunction, and spatial configuration search data from the first paper. We used an iterative Kolmogorov-Smirnov cluster analysis to determine which distributions should be combined or kept separate. The most striking finding is that, while there are some reliable differences between specific conditions, the great majority of these normalized distributions cluster together and share a common underlying shape across variations in set size and target presence or absence. This finding has implications for theories of search. For example, if your model predicts that RT distributions should change in shape as a function of set size, your model is wrong. Regrettably, it is hard to find a model that does not predict such a change. This remains an interesting problem for modeling. The easy way out would be to imagine that the shape of the RT function is driven largely by non-search components but this does not seem terribly plausible.

We have posted the data from these papers on our website so that anyone else who wants to model RT distributions will have the distributions to model.
http://search.bwh.harvard.edu/new/data_set.html

Palmer, E. M., Fencsik, D. E., Flusberg, S. J., Horowitz , T. S., & Wolfe, J. M. (2009). Crossing Over: Can Set Size Effects In Visual Search Be Explained By A Single Decision Rule? *Attention, Perception, and Psychophysics, submitted, in revision 9/08*

This paper represents another effort to make a qualitative distinction between two broad classes of visual search models. Attention-limited models propose two stages of perceptual processing: an unlimited capacity preattentive stage and a limited-capacity selective attention stage. Conversely, noise-limited models propose a single unlimited capacity perceptual processing stage, with decision processes limited by perceptual signal quality.

In this study, we arranged for a feature search to be harder than a spatial configuration search for a set size of one (not really a search at that point). Stimuli were presented briefly so the measures of interest were accuracy and related signal detection measures, notably, d'. Now consider what should happen if set size is increased. A single stage, parallel processing model, will predict that, if task A is harder than B at set size 1, it must remain harder at all set sizes. In contrast, a two-stage model (e.g. Guided Search) makes a different prediction. Performance on the easier spatial configuration search degrades more rapidly as set size goes up because the initial guidance stage does nothing useful for that search. By contrast, front-end guidance can help a second decision stage in the feature search task. The prediction would be a crossover interaction with spatial configuration easier at small set sizes and feature search easier at larger set sizes.

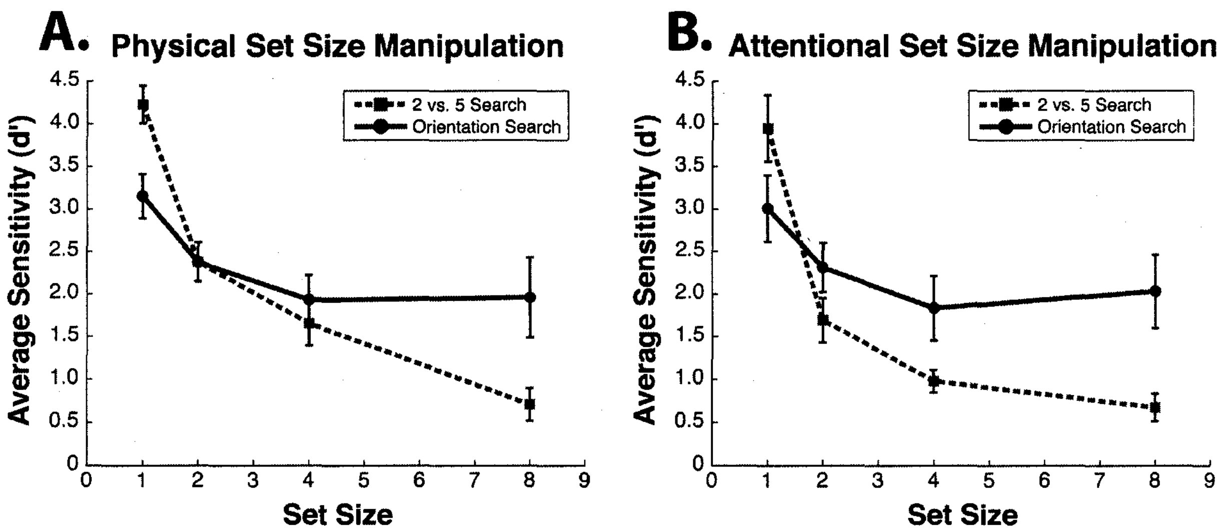

Figure Three: Results from the Palmer et al. "cross over" experiment.

Figure Three shows the results from two versions of this experiment. The data show the clear cross-over interaction predicted by Guided Search. The useful feature of this experiment is its qualitative nature. A cross-over interaction rules out a whole class of models without the need engage in detailed curve fitting or parameter estimation. If your model proposes that search for an item of one orientation and search for a 2 among 5s are both done by a parallel process with a single decision rule, then these data will be a problem for your model.

Wolfe, J. M., Horowitz , T. S., Palmer, E. M., Michod, K. O., & VanWert, M. J. (2007). Getting In To Guided Search. In V. Coltheart (Ed.), *in press*.

Consider a search for a red letter "T" among red and black letters. How is attention guided to red items? There are several views of how this guidance might be implemented in the visual system. First, it could be that top-down guidance acts like a filter, placed across the input stream for an entire block of trials, effectively passing only items of the correct color as candidates for attention as in Figure 4, below.

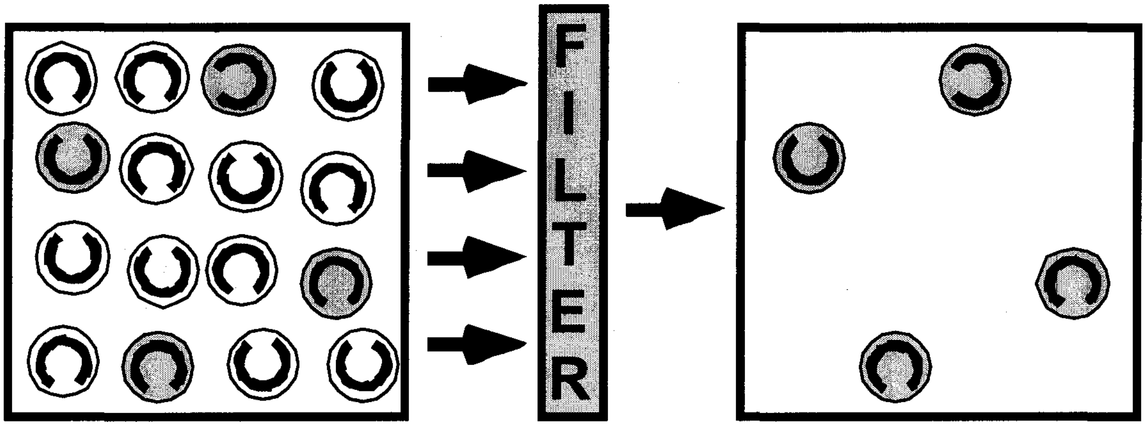

Figure Four: Guidance as a filter

Alternatively, all items might be initially passed up the visual pathway, with top-down guidance intervening only after a delay or in some feedback process to weed out items of the wrong color.

Figures Five and Six illustrate an approach to this problem that we took in a set of experiments. The observer was faced with a set of Cs in four possible orientations. All but one opened up or down. The target, present on each trial, opened to the left or right, and observers were asked to report its orientation. Each C was placed on a colored disk. Suppose that observers knew that the target was always on a gray disk (We used color in the actual experiment). If the top-down guidance to gray acted like a persistent filter, then that filter should reduce the effective set size to the set of four gray items. If no guidance were available, this would be a search through the 16 Cs on the left side of the figure.

To examine the temporal dynamics of guidance, we varied the time of onset of the colors relative to the onset of the Cs (Figure Five).

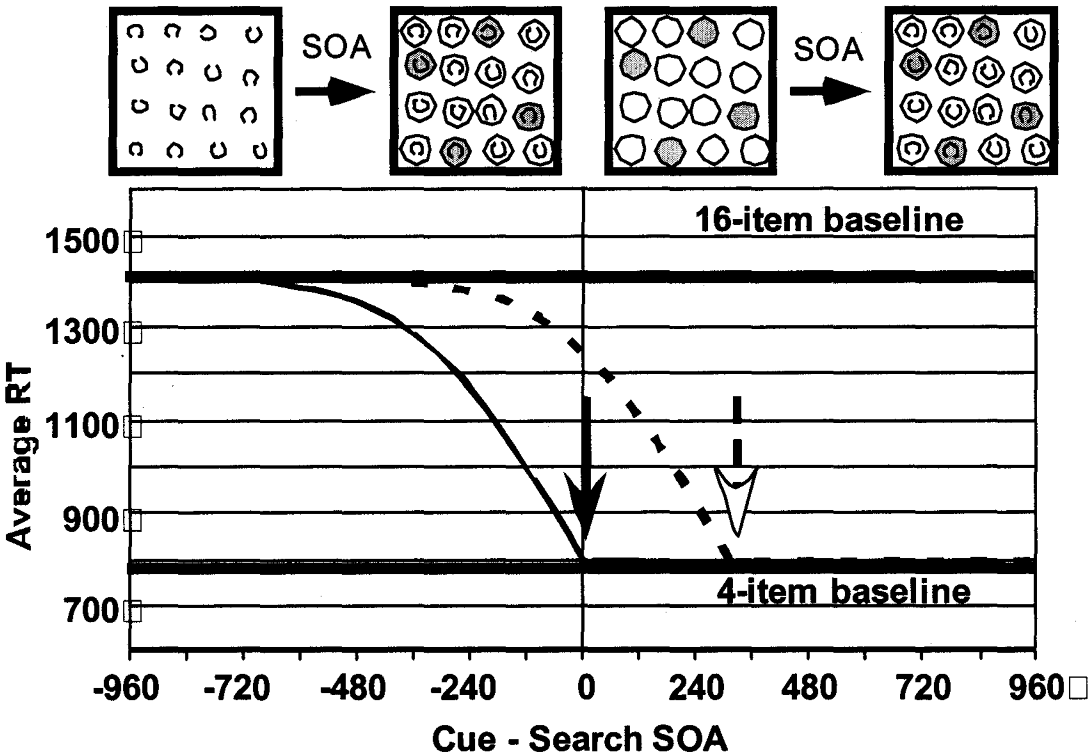

Figure Five: Hypothetical outcomes for the time-to-guide experiments. Solid line assumes that color guidance is available as soon as the color is available. Dashed line assumes that guidance begins about 300 msec after the color becomes available.

Consider a simple, two-state model. At any moment, observers are either searching through all 16 items in an unguided manner, or they are restricting their search to the four items of the target color. For simplicity, assume that there is a sharp transition between those two states. Suppose that the Cs appear 400 msec before the color cue (SOA = -400 in Figure Five). When the Cs appear, observers must begin by searching through 16 items because there is no guiding information. After 400 msec, the color information appears. Once it becomes effective, this becomes a search through four items. The RT, therefore, is a mixture distribution of some purely unguided searches, when the observer finds the target before the color ever appears, and some that benefit from eventual guidance. As the SOA becomes increasingly negative, there is a greater chance that the search will finish before the color becomes available. At the longest negative SOAs, RTs should approximate the 16-item baseline, the time required to find a target when there is no color guidance. The four-item baseline is the RT for an unguided search through a set of just four items.

The solid curved line in the bottom half of Figure Five illustrates the prediction if guidance starts as soon as the guiding information is presented (solid line). For any positive SOA, the task looks like search through just 4 items. The dashed line shows what the results would look like for a hypothetical 300 msec delay in guidance. The search doesn't look like a 4-item search until the colors precede the Cs by 300 msec.

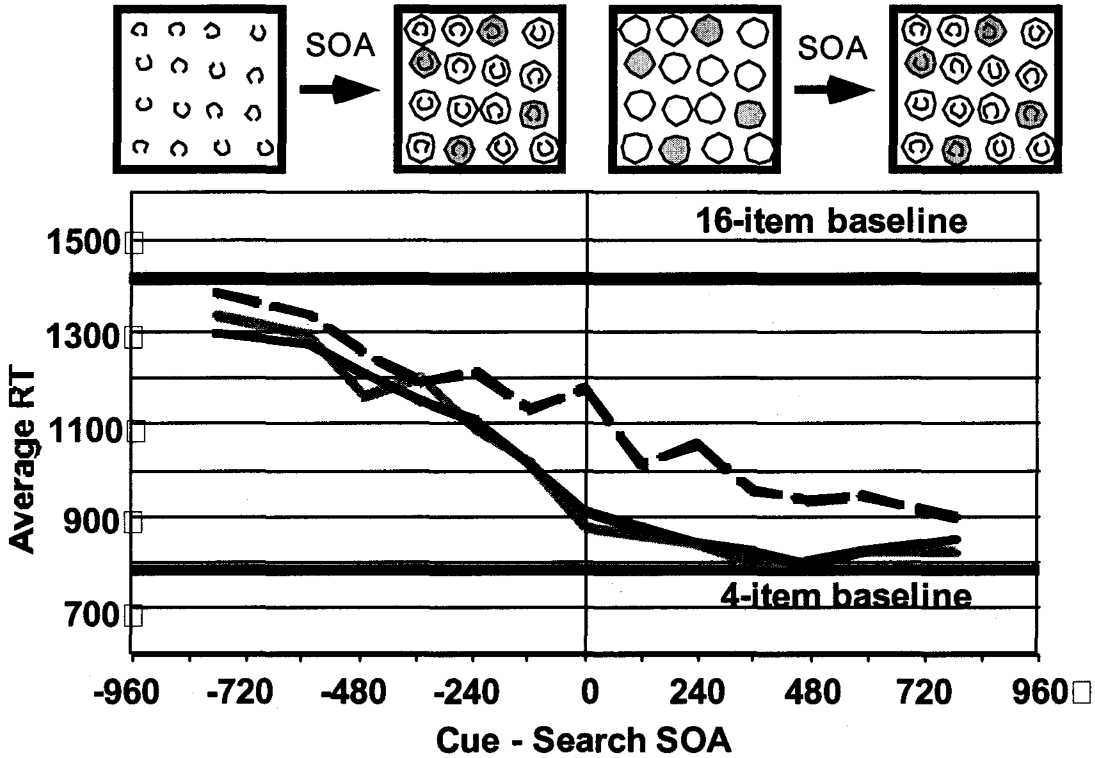

Figure Six: Results for one set of time-to-guide experiments. Black line shows data from Blocked trials. Gray line shows data for Mixed trials with consistent mapping of target and distractor colors. The dashed line shows data for Mixed trials with inconsistent mapping.

Figure Six shows average of the median RTs for 15 observers. Each observer was tested for 30 trials at each of 13 SOAs. Each observer also completed 27 trials of unguided search with set sizes of 4 and 16 items to establish the baselines, plotted as horizontal lines at their median value.

The most important data are those plotted in black. They show the results for a blocked condition where observers knew that the 4 item subset containing the target would always be the same color (e.g. "Look for red"). The 12 distractors also preserved the same distractor color for the entire block. Performance at SOA 0 is significantly above the baseline. This argues that, even under conditions when an observer can maintain the same 'guiding principles' for an entire block of hundreds of trials, guidance takes time to develop on any given trial. Apparently, when the stimuli first appear, everyone is passed through as a candidate target. Only after 200-300 msec does guidance become fully effective.

The gray line shows a consistent mapping condition in which Os knew that some colors (e.g. red, purple, blue) were target colors and others (e.g. yellow, green, cyan) were distractor colors but where the specific colors could vary from trial to trial. This produces similar results to the blocked condition. In contrast, the dashed line shows data from conditions where Os knew only that the target would be in the smaller color subset but the colors changed at random from trial to trial. Under these conditions, full guidance took

much longer to establish. This can be considered to be a version of a switch cost (Wylie & Allport, 2000) (Mayr & Kliegl, 2003).

Guiding Features

As part of the effort to understand guidance, we carried out several series experiments on the attributes that might guide attention. We describe these briefly here:

Horowitz, T. S., Wolfe, J. M., DiMase, J., & Klieger, S. B. (2007). Visual Search For Type Of Motion Is Based On Simple Motion Primitives. Perception, 36, 1624-1634.

We know that motion is a basic guiding attribute (e.g. find the moving item among stationary) (Dick, Ullman, & Sagi, 1987; McLeod, Driver, & Crisp, 1988). Here we asked if it is possible to search for items based on their type of motion? We examined three types of motion: 1) ballistic motion, in which objects move in a straight line until they encounter an obstacle; 2) random walk motion, in which objects change direction randomly; 3) composite motion, in which objects move with random fluctuations around a generally ballistic trajectory. The data, a complicated pattern of search asymmetries, can be modeled if we assume that Os can guide attention using processes sensitive to the presence of linear motion and change in motion. The results do not support the idea that we have a more sophisticated ability to segregate items based on the nature of their motion.

Li, X., Cave, K., & Wolfe, J. M. (2008). Kanisza-Style Subjective Contours Do Not Guide Attentional Deployment In Visual Search But Line Termination Contours Do. *Perception & Psychophysics,* 70(3), 477-488.

In these experiments, we considered whether attention could be guided by Kanizsa-type subjective contours and by subjective contours induced by line ends. This is a topic with some history (Davis & Driver, 1994; Davis & Driver, 1998; Gurnsey, Humphrey, & Kapitan, 1992; Gurnsey, Poirier, & Gascon, 1996). In our work, unlike in previous experiments, we compared search performance with subjective contours against performance with real, luminance contours. Moreover, observers searched for shapes and orientations or shapes created by the subjective contours, rather than searching for the presence of the contours themselves. We replicated the usual finding that visual search for one orientation or shape among distractors of another orientation or shape was efficient when the items were defined by luminance contours. Search was much less efficient among items defined by Kanizsa-type subjective contours. However, search remained efficient when the items were defined by subjective contours induced by line ends. This may reflect a difference in the underlying neural computations that support these types of subjective contours.

Wolfe, J. M., Reijnen, E., Van Wert, M. J., & Kuzmova, Y. (2009). In Visual Search, Guidance By Surface Type Is Different Than Classic Guidance. *Vision Res*, 49(7), 765-773.

These experiments involved stimuli like those shown here in Figure Seven. Os search for a T among Ls. We could provide "classic" guidance by telling Os that the T, if present, would be yellow. Alternatively, we could guide to the surface. Here, the cue would be that the T was on a left-facing surface. We can certainly us some sort of surface guidance in the world. If you were asked to look for a painting, you would look on walls, not floors or ceilings, for example. We wanted to know if the two forms of guidance are equivalent. As the title of the paper states, they are not. When a target can lie on one of many surfaces, color guidance is effective but surface guidance is not (Exp. 1-3 of the paper). We found that there was effective guidance to multiple cubes if all those cubes were coplanar. In that case, Os could guide to the coplanar tops of the cubes (Exp. 4). Similarly, Os could guide to a limited number of surfaces (Exp. 5). We believe that, while surface guidance must exist, it is slow compared to color guidance and seems to be limited to fewer surfaces at one time.

QuickTime™ and a
decompressor
are needed to see this picture.

Reijnen, E., Pedersini, R., Pinto, Y., Horowitz , T. S., & Wolfe, J. M. (2009). Pre-Attentive Processing Of Occlusion Information In Visual Search. *Attention, Perception & Psychophysics, ms (submitted Feb 09).*

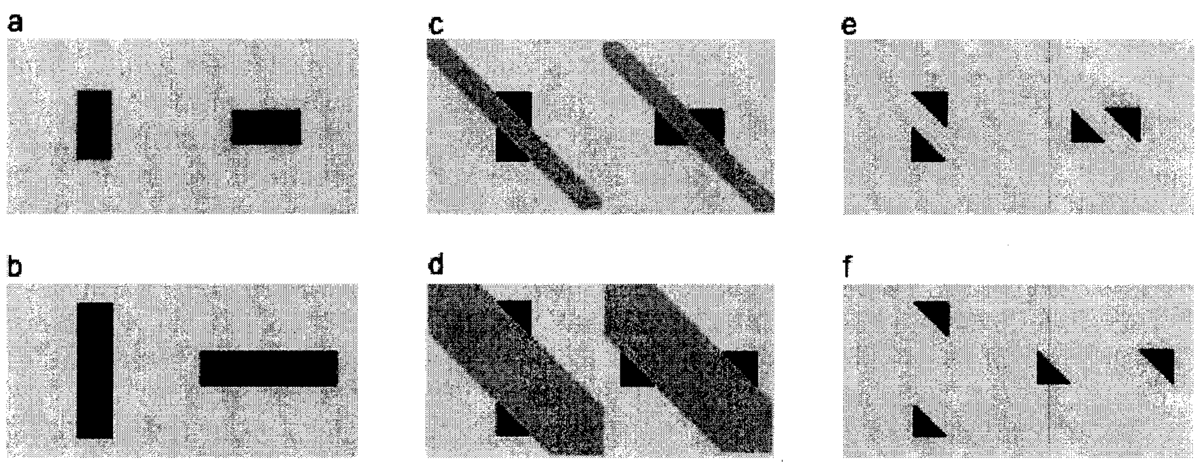

Figure Eight: Do occluded bars behave like 'real' bars in visual search.

In this project, we were concerned with the ability of preattentive processes to complete contours behind occluders. Searching for vertical among horizontals using stimuli like those in Fig. 8a,b is very easy. What about the stimuli in 8c,d? Is the orientation of those occluded bars available to guide search or not. Fig 8e,f show stimuli for control conditions. In a rather long series of experiments, we have found that it is possible to create conditions where the occluded bars support efficient search and the control conditions do not. However, the effect is rather fragile suggesting that the orientation signal created by those occluded bars is rather weak.

Contextual Cueing

About 10 years ago, Chun and Jiang (1998) described a new phenomenon that they called "contextual cueing". They showed that RTs became faster if the same search displays were repeated. Observers learned something about the displays even though theses were random collections of meaningless stimuli (e.g. Ts among Ls). Chun and Jiang (and many others since) argued that this was a form of guidance. The believed that Os were implicitly learning that they should guide attention to *this* location in the presence of *this* arrangement of items. Such a phenomenon with such an explanation is of obvious relevance to our Guided Search project.

Kunar, M. A., Flusberg, S. J., Horowitz, T. S., & Wolfe, J. M. (2007). Does Contextual Cueing Guide The Deployment Of Attention? J Exp Psychol Hum Percept Perform, 33, 816-828.

Most of the work on contextual cueing (CC) had used mean RT as the measure of interest. However, if one is interested in guidance, the critical measure is the slope of the RT x set size function. Indeed, if CC provided perfect guidance, slopes should drop to zero. The display configuration would point the observer directly to the target, regardless of the number of distractors present. We did an extensive series of CC experiments with set size manipulations and simply could not find an effect of CC on search efficiency. We could replicate the basic CC effect on RT but the slope did not change. We, reluctantly, conclude that CC is not a form of guidance. Our guess is that it is a form of response priming. You are a bit faster to say that the target is the target if it is in a familiar setting.

Kunar, M. A., Flusberg, S. J., & Wolfe, J. M. (2007). Time To Guide: Evidence Tor Delayed Attentional Guidance In Contextual Cueing. *Visual Cognition*, 16, 804-825.

At some level, we must be wrong about this. You can certainly use your overt knowledge of a scene to guide your attention. You look for your coffee maker in a specific location because you have learned and remembered that context. The issue might be one of time scale. In another series of experiments, we found that we could get a form of CC guidance if we slowed search. If there was enough time, knowledge about the layout of a display could be used to direct attention to target locations.

Kunar, M., Flusbuerg, S., & Wolfe, J. (2006) Contextual Cueing By Global Features. Perception & Psychophysics, 68(7), 1204-1216

We extended the CC phenomenon to what we call global features. For the bulk of the studies report here, the global feature was color. This meant that, if the display was red, the target could be found in one location. If it was blue, the target was consistently presented in another location, and so forth. The results are similar in their essentials to the classic CC. Os could learn the association between color and target location. This learning speeded RTs but did not change the slope of the RT X set size function, suggesting no

guidance. However, if a relatively long delay intervened between the appearance of the global cue and the start of the search, then search efficiency could be improved.

Kunar, M. A., & Wolfe, J. M. (2008). No Target No Effect: Target Absent Trials In Contextual Cueing. in revision.

One final piece of information about contextual cueing: Nothing seems to be learned on target absent trials. On the face of it, there is no good reason why Os should not learn that *this* display configuration means that there no target. However, that does not seem to be the case.

Microsaccades

Horowitz, T. S., Fine, E. M., Fencsik, D. E., Yurgenson, S., & Wolfe, J. M. (2007). Fixational Eye Movements Are Not An Index Of Covert Attention. *Psychol Sci, 18*(4), 356-363.

Horowitz , T. S., Fencsik, D. E., Fine, E. M., Yurgenson, S., & Wolfe, J. M. (2007). Microsaccades And Attention: Does A Weak Correlation Make An Index? Reply To Laubrock, Engbert, Rolfs, & Kliegl (2007). *Psychol Sci, 18*(4), 367-368.

One of our long-time fantasies has been that someone would develop a "covert attention tracker", akin to an eye tracker. If we assume that it is being deployed from item to item, covert attention is being deployed at a rate of something like 20-40 Hz. Under most circumstances, the deployment of the eyes is closely tied to the deployment of attention but at a slower rate of 3-4 Hz. Thus, we were excited by reports that microsaccadic eye movements might serve as pointers to the loci of covert attention (Engbert & Kliegl, 2003). Unfortunately, in our hands, as the title says these "eye movements are not an index of covert attention." This is not a settled issue (hence the second article). However, we still await a method that would allow tracking of covert attention within a trial.

AIM 2: **Understanding the role of memory in visual search:** Standard serial models of attention have assumed that items in the display are sampled *without* replacement. In the previous grant period, we have shown that the data reject this assertion of perfect memory for rejected distractors. We have proposed that items are sample *with* replacement in typical search tasks. Data from other labs suggest the possibility that some partial memory (perhaps oculomotor) discourages deployment to recently attended items. In the next grant period, we will investigate the theoretical and practical consequences of visual search with limited memory for previous deployments of attention.

Several aspects of the role of memory in visual search have interested us during the grant period. The original roots of our interest lie in our 1998 finding that, as we put it, "Visual search has no memory." (Horowitz & Wolfe, 1998). This claim was based on a series of experiments in which items in a visual search task were randomly repositioned every 100 msec (or every 500 msec in some experiments). This makes it impossible to mark rejected distractors. If it were the case that rejected distractors were marked to eliminate them as candidate targets in normal search, then random replotting should make search efficiency significantly worse. In fact, search efficiency is about the same in the standard static and the dynamic, replotting conditions.

Horowitz, T. S. (2006). Revisiting The Variable Memory Model Of Visual Search. *Visual Cognition, 19*(4-8), 668-684.

Horowitz, T. S., & Wolfe, J. M. (2005). Visual Search: The Role Of Memory For Rejected Distractors. In L. Itti, G. Rees & J. Tsotsos (Eds.), *Neurobiology of attention* (pp. 264-268). San Diego, CA: Academic Press / Elsevier.

Our claim of no memory for rejected distractors has proven controversial (Beck, Peterson, & Vomela, 2006; Dukewich & Klein, 2005; Kristjansson, 2000; McCarley, Wang, Kramer, Irwin, & Peterson, 2003; Peterson, Kramer, Wang, Irwin, & McCarley, 2001; Shore & Klein, 2000; von Muhlenen, Muller, & Muller, 2003). Though we continued to find no reliable evidence for marking of rejected distractors (Horowitz & Wolfe, 2001), others, using different methods, found some. There are various possibilities. It may be that there is memory attached to the deployment of the eyes, if not to the deployment of covert attention. It may be that there is some memory for a few deployments of covert attention. Our position, as argued in the papers noted here, is that a reasonable consensus might be that "visual search has *very little* memory". It may have just enough to prevent perseveration in search. If there is nothing biasing observers away from recently visited items, it is hard to see why attention doesn't get stuck on the most salient item in the field.

Memory & Search In Autistic Observers

Joseph, R. M., Keehn, B., Connolly, C., Wolfe, J. M., & Horowitz , T. S. (2009). Why Is Visual Search Superior In Autism Spectrum Disorder? Developmental Science, in press, (available on-line).

Special populations of observers can provide insight into the mechanisms of search. It is interesting, therefore, to find that individuals diagnosed with Autism Spectrum Disorder (ASD) outperform controls on visual search tasks (O'Riordan, Plaisted, Driver, & Baron-Cohen, 2001; Plaisted, O'Riordan, & Baron-Cohen, 1998). We wondered if this was due to superior memory for rejected distractors. Maybe visual search does have memory in the autistic population.

To assess this possibility, we compared the performance of 21 children with ASD and 21 age- and IQ-matched typically developing (TD) children in a standard static search task and a dynamic search task, like those describe above, with targets and distractors randomly

changing positions every 500 ms. The ASD observers had faster RTs than the TD children. However, as in our previous work, they showed no disruption in search efficiency in the dynamic condition. If they had memory for rejected distractors in the static search conditions, then they should have had elevated RT x set size slopes in the dynamic case. Thus, it seems unlikely that memory for rejected distractors is the source of the enhanced visual search abilities in the ASD group.

While there were differences in slopes, there were lower intercepts for the ASD group in both static and dynamic search, suggesting that the ASD group has an advantage in some non-search processes. We suspect that they are faster to determine if the current object of attention is a target or a distractor. We gain some support for this from eye-movement data. ASD and TD groups produced similar in numbers and spatial distributions of fixations. However, fixation duration was in the ASD group as if they needed to spend less time on each fixation.

Why Don't We Use Memory?

Kunar, M. A., Flusberg, S. J., & Wolfe, J. M. (2008). The Role Of Memory And Restricted Context In Repeated Visual Search *Percept Psychophys*, 70(2), 314-328.

As noted above, all of these failures to show an influence of memory are a bit mysterious since it is self-evidently true that we can use memory in search. We explored this puzzle in a follow-up on studies of repeated search (largely the topic of a different grant and not extensively discussed here). The core observation is that search efficiency remains essentially unchanged even when Os search through the same, unchanging display hundreds of times (Wolfe, Klempen, & Dahlen, 2000). In our standard, repeated search experiments, Os search through an array of letters. Why doesn't the search become more efficient? Certainly Os know where the "K" or the "Q" are after a few dozen trials. They could do the task with there eyes closed. We didn't have Os close their eyes. We simply removed the display and had Os make a localizing mouse click on the remembered location of the target letter. When Os make these localizing responses on visible displays, the slope of the RT x set size function is about 35 msec/item. Os can do the task with memory, but the slope is about 100 msec/item. So, here is a case where Os do not use memory because it is too slow. It is more efficient to do the visual search de novo than to rely on memory.

Similarly, within a search, we suspect that memory processes are slow. They do not play a role in a standard, laboratory search for a T among Ls. However, in a real world search, strategic planning can play a role (e.g. I remember looking on the desk. The keys were not there. I will turn my attention to the sofa.)

AIM 3: **The relationship of different modes of attentional control.** There are multiple processes that can control attention. Some of these appear to be very fast. Others are closely coupled with eye movements. The work in Aim 3 is intended to determine how these share control of visual attentional resources.

In the lab, we tend to examine search (or other processes) in relative isolation. In the world, several tasks may be running at the same time. The papers described in this section are united by their concern with the interaction of search with other processes.

Horowitz, T. S., Wolfe, J. M., Alvarez, G. A., & Kenner, N. M. (in press). The Speed of Free Will. *Quarterly Journal of Experimental Psychology*

We begin with a set of experiments on what we, somewhat expansively, call "free will". The original question grew out of our work on memory in search. Recall that our data show little or no memory for the course of a search. This seems odd. In a random display where the target could be anywhere, one could produce the same benefits offered by perfect memory if one merely searched the display in order. Any order will do, but one can imagine "reading" the array from upper left to lower right. In an earlier paper (Wolfe, Alvarez, & Horowitz, 2000), we compare search under conditions that allowed covert attention to be deployed in each usual anarchic manner to other conditions in which attention was moved by an act of volition from item to item. We estimated the time required for each type of deployment and found that anarchic deployments were fast (35-100 msec per shift) while volitional deployments were slow (200-300 msec per shift).

The 2000 paper was a very short report. In the 2009 paper, we report on a much more extensive set of experiments that provide converging evidence for this point. Volitional control of the deployments of attention is possible but it is much slower than the free-running deployments that occur when our personal "search engine" is given a task and left to solve it in any manner it chooses. It seems more than coincidental that the speed of volitional attentional deployments is very similar to the rate of saccadic eye movements. We suspect that the underlying mechanisms are related.

Horowitz, T. S., Holcombe, A. O., Wolfe, J. M., Arsenio, H., & DiMase, J. S. (2004). Attentional Pursuit Is Faster Than Attentional Saccade. *Joural of Vision, 7*(6), 585-603.

Pursuing this connection between movements of the eyes and movements of attention, we devised a task in which attention either made ballistic (saccadic) movements from point to point or tracked a moving target (pursuit). We found that pursuit was faster than saccadic jumps in this case. The broader point is that the control of attentional pursuit is different than the control of attentional saccades.

Alvarez, G. A., H. C. Arsenio, et al. (2005). Do Multielement Visual Tracking And Visual Search Draw Continuously On The Same Visual Attention Resources? J. Exp Psychol Hum Percept Perform **31**(4): 643-667.

Multiple object tracking (MOT) can be thought of a form of attention pursuit. In a display of several identical items, a subset is briefly highlighted. All items then begin to move and the observer's task is to track the designated subset. This task certainly takes 'attention'. How is the resource, used in MOT, related to the attentional resources required in visual search? To answer this question, we had Os perform both tasks during a single trial. Os

began tracking a set of dots. At some point, a search array appeared and Os were asked perform a search task while still being able to report on the tracked set when asked later. We used an "attentional operating characteristic" (AOC) method to determine if the two tasks interfered with each other (Sperling & Melchner, 1978). Measured in this manner, we found that the two tasks did not interfere any more than other essentially independent tasks.

We did notice that RTs in the search task were much longer when Os were also tracking. We developed the hypothesis that Os can task switch between search and MOT. In effect, it is possible to *put down* the tracked balls, perform a few hundred msec of search, and then return to the MOT task. This observation is sufficiently interesting that it has lead to an separate line of investigation. The primary funding for that work comes from another grant. However, it can be seen as a logical extension of the work in Aim 3 on the interaction of different modes of attention. The primary publications in this line are shown below.

Wolfe, J. M., Place, S. S., & Horowitz, T. S. (2007). Multiple Object Juggling: Changing What Is Tracked During Extended Multiple Object Tracking. *Psych Bulletin & Review, 14*(2), 344-349.

Horowitz, T. S., Klieger, S. B., Fencsik, D. E., Yang, K. K., Alvarez, G. A., & Wolfe, J. M. (2007). Tracking Unique Objects. *Perception & Psychophysics, 69*(2), 172-184.

Horowitz, T. S., Birnkrant, R. S., Wolfe, J. M., Fencsik, D. E., & Tran, L. (2006). How Do We Track Invisible Objects? Psych. Bull. And Rev., 13(3), 516-523.

Fencsik, D. E., Klieger, S. B., & Horowitz , T. S. (2007). The Role Of Location And Motion Information In The Tracking And Recovery Of Moving Objects. Percept Psychophys, 69(4), 567-577.

CHAPTERS

Finally, we note that AFOSR funding was instrumental in the preparation of several review chapters on visual search:

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Wolfe, J. M. (2009). Visual Search: Is It A Matter Of Life And Death? In M. A. Gernsbacher (Ed.), Psychology and the Real World: Essays Illustrating Fundamental Contributions to Society, October 2008: Worth.

Howe, P. D., Evans, K. K., Pedersini, R., Horowitz , T. S., Wolfe, J. M., & Cohen, M. (2009). Attention: Selective Attention And Consciousness. In W. P. Banks (Ed.), *Encyclopedia for Consciousness*. (Vol. 1, pp. 61-75). Oxford: Elsevier, UK.

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